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SURVEY

Toward Sleep Spindle Detection: A Comparative Survey of State-of-the-Art, Challenges and Future Research

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ABSTRACT Automatic sleep spindles are hallmark EEG features of non-REM stage 2 sleep and play a crucial role in maintaining sleep stability, consolidating memory, and promoting neurocognitive development. Accurately detecting these oscillations is essential for clinical diagnostics and neuroscience research. Background: Over the past years, the landscape of automatic sleep spindle detection has evolved from traditional signal processing techniques to machine learning and deep learning techniques. This change has been driven by the growing availability of large EEG datasets and the demand for automated, reproducible analysis methods. Despite the significant progress, inconsistencies in detection standards, dataset limitations, and model interpretability remain open challenges. Research Aim: This survey aims to systematically review, classify, and compare state-of-the-art techniques for automated sleep spindle detection. Key research questions on methodological evolution, performance metrics, dataset utilisation, and future development needs guide the survey. Research Methodology: A structured methodology was followed, including a keyword-based search across major academic databases, inclusion/exclusion criteria, and a four-step paper selection process. Result: Our analysis categorised detection methods into three main approaches: traditional, ML-based, and DL-based, with a comparative evaluation based on accuracy, sensitivity, F1-score, and dataset generalizability. Benchmark datasets such as MASS, DREAMS, and Sleep-EDF are discussed in detail. The discussion section comprehensively summarises the survey from the perspectives of interpretability, generalizability and clinical implementation. Conclusion and Future Research: This survey concludes that while DL techniques currently yield the highest detection performance, they lack interpretability and require large labelled datasets. Future work will focus on implementing and benchmarking ML-based approaches on standardised EEG datasets like MASS and DREAMS to enhance practical usability and generalisation.

INDEX TERMS Sleep spindles, electroencephalography, REM sleep, sleep disorders, neurophysiological, machine learning, deep learning.

I. INTRODUCTION

Sleep spindles are momentary bursts of oscillatory brain motion in the sigma frequency between 11 and 16 Hz that predominantly occur in stage N2, such as non-rapid eye movement (NREM) sleep [1], [2]. They typically last for at least 0.5 seconds and fall within a frequency range of 11 to 16 Hz [3], although this range can vary depending on factors like the age of the individuals studied [4]. According to the American Academy of Sleep Medicine (AASM) [3] *Manual for the Scoring of Sleep and Associated Events*, a sleep spindle is formally defined as "a train of distinct waves

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with a frequency of 11–16 Hz (most commonly 12–14 Hz), with a duration of ≥0.5 seconds, and typically maximal in amplitude over the central regions of the scalp.'' A higher spindle density—defined as the number of spindle events per hour of N2 and N3 sleep—has been linked to greater resistance to stress-induced insomnia [5], as well as stronger cognitive abilities [6], [7] and improved overnight memory retention [8]. These periodic patterns are of considerable interest in sleep and neuroscience studies due to their importance in memory consolidation, brain development, cognitive functions, and synaptic plasticity. Identifying, understanding and precisely detecting sleep spindles is essential for advancing scientific research in brain-state-dependent interventions, neurodevelopmental conditions, and sleep disorders. However, the inter-individual variability, transient nature, and overlapping with other EEG waveforms present significant challenges in developing precise and robust detection methodologies.

Additionally, notable changes in spindle characteristics have been reported in individuals with conditions such as sleep apnea [9], Alzheimer's disease [10], and schizophrenia [11]. Collectively, these associations suggest that spindles play key roles in sustaining sleep, supporting intellectual development, aiding memory consolidation, and promoting brain plasticity.

Sleep spindles were initially characterised by [12] as rhythmic brainwave patterns in the 12–14 Hz range, lasting between 0.5 and 3 seconds and exhibiting a waning and waxing morphology [13]. These oscillations generally appear in full-term infants around 6 to 8 weeks of age [14]. As children grow, notable developmental changes in spindle characteristics occur, making them valuable indicators of functional brain maturation [6]. Researchers have suggested that sleep spindles reflect early central nervous system development [15] and may play a role in neuroplasticity during infancy [16]. Furthermore, they are closely associated with memory processes [17]; for instance, higher spindle density in the left frontocentral region has been linked to improved overnight verbal memory retention [8]. Consequently, disruptions in standard spindle patterns could serve as early markers of atypical neurodevelopment. Despite their clinical relevance, manual spindle detection in infant EEG recordings remains labour-intensive, and progress in automated detection methods for this population has been limited [18], [19].

In the past, sleep spindle detection depended on expert manual annotation, which was time-consuming, subjective, and prone to inconsistencies [20]. On the other hand, traditional automated methods have primarily leveraged frequency-domain, time-domain, and time-frequency domain characteristics to identify sleep spindles [21]. The emergence of machine learning (ML) and deep learning (DL) approaches provides more accurate and scalable solutions. This research survey comprehensively compares classical and modern sleep spindle detection methodologies, highlighting their strengths, limitations, challenges and future research directions.

A. IMPORTANCE OF SLEEP SPINDLES IN NEUROSCIENCE AND SLEEP STUDIES

Sleep spindles function as essential markers of cognitive functioning and sleep stability. Several research studies have linked sleep spindles to neuroplasticity, memory consolidation, and learning enhancement. Existing research suggests that spindle movement has been correlated with intelligence measures, suggesting a role in learning efficiency and cognitive performance. Moreover, sleep spindles facilitate communication between the cortex and thalamus, promoting long-term synaptic potentiation, a process essential for memory formation.

In addition to cognitive functions, sleep spindles are associated with psychiatric and neurological disorders [22]. Unusual spindle movement has been detected in conditions such as autism spectrum disorder (ASD), schizophrenia, and Alzheimer's disease, which highlights their capability and assists in biomarkers for early-stage diagnosis and treatment monitoring [23]. In the case of schizophrenia, spindle shortfalls have been correlated to disrupted thalamocortical connectivity and impaired cognitive function. Correspondingly, spindle modifications in neurodevelopmental disorders are associated with brain maturation processes. Considering its importance and significance, identifying and detecting sleep spindles in EEG recordings is essential for advancing clinical applications and fundamental neuroscience [24].

Figure 1 provides an overview of the different segments of the sleep cycle, highlighting their categories and descriptions. Understanding these stages is crucial for recognizing the importance of sleep in overall health and well-being. N1: Category: Light Sleep is the transitional sleep stage between wakefulness and sleep. During this phase, the body begins to relax, and brain activity starts to slow down. It typically lasts only a few minutes and is characterized by a light level of sleep where one can be easily awakened. N2: Category: Light Sleep represents the largest portion of the sleep cycle. This stage is characterized by the presence of sleep spindles and K-complexes, which are bursts of brain activity that help protect sleep and aid in memory consolidation. N2 plays a vital role in preparing the body for deeper sleep stages. N3: Category: Deep Sleep, also known as slow-wave sleep, N3 is crucial for physical restoration and recovery. During this stage, the body undergoes significant repair processes, including tissue growth and muscle recovery. It is the deepest stage of sleep, making it difficult to awaken someone in this phase. REM (Rapid Eye Movement): Category: Vivid Dreaming is characterized by rapid movements of the eyes and is critical for memory consolidation and emotional processing. This stage is where most vivid dreaming occurs, and it plays a significant role in cognitive functions and emotional regulation.

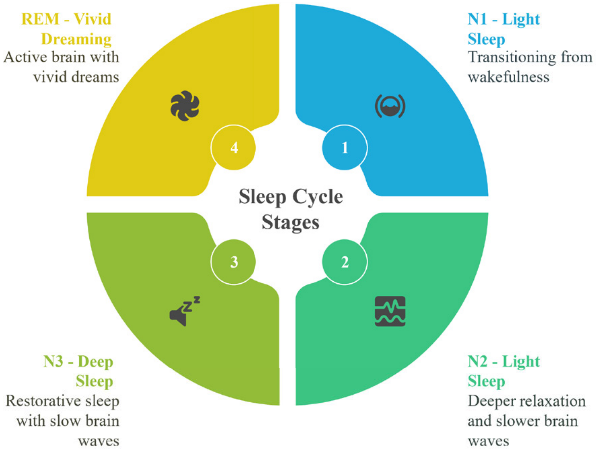

FIGURE 1. The Sleep Cycle.

The study [25] introduces MuRAt-CAP-Net, a deep learning model designed for automatic detection of Cyclic Alternating Pattern (CAP) A-phase and its subtypes (A1, A2, A3). Unlike manual scoring, which is complex and reliant on experts, MuRAt-CAP-Net uses a multi-input residual attention architecture that processes signals from four EEG channels simultaneously. Attention mechanisms are incorporated to emphasise the most relevant features. In [26], the authors present a comprehensive review of 36 studies (2013–2020) that applied deep learning (DL) models for automatic sleep stage classification using overnight polysomnogram (PSG) recordings. The review highlights that the study emphasises that DL-based programmed diagnostic tools (PDTs) show strong potential for the timely and accurate detection of sleep disturbances. However, future systems must integrate multimodal PSG data rather than EEG alone to ensure robustness for clinical deployment. Sleep spindle detection is not only pivotal for understanding core neurocognitive functions, such as memory consolidation and brain plasticity [27], but also serves as a biomarker for sleep quality and neurological health [28]. Furthermore, alterations in spindle characteristics are increasingly recognised in the diagnosis and monitoring of neuropsychiatric and neurodegenerative disorders [29]. Beyond its diagnostic relevance, spindle detection underpins a diverse range of clinical and research applications [30], including the evaluation of therapy, the development of brain-computer interfaces, and sleep-based cognitive enhancement strategies. Table 1 presents a comprehensive summarized version of all of the discussed neuroconnitive functions from the perspective of sleep spindles detection.

B. OVERVIEW OF TRADITIONAL AND MODERN APPROACHES (ML AND DL)

The advancement of sleep spindle detection methodologies can be classified into traditional and modern artificial intelligence-based (machine and deep learning) methods.

TABLE 1. Sleep Spindles Detection: Neurocognitive Functions, Biomarker for Sleep Quality and Brain Health, Diagnosis and Monitoring of Neurological Disorders, and Clinical and Research Applications.

Aspect	Details
Neurocognitive Functions	
Memory Consolidation	Sleep spindles play a crucial role in consolidating both declarative (factual) and procedural (skill-based) memories. Higher spindle density often correlates with better memory performance [31].
Cognitive Development	In children and adolescents, spindle activity correlates with brain maturation and cognitive abilities such as reasoning and problem-solving [32].
Learning Enhancement	Spindle-rich sleep periods are crucial for integrating new learning into long-term memory, especially following intensive training or study sessions [27].
Biomarker for Sleep Quality and Brain Health.	
Sleep Architecture	Spindles are markers of N2 sleep stage stability and quality. Their presence indicates a healthy progression through sleep stages [33].
Brain Plasticity	Spindle dynamics are linked with synaptic plasticity—the brain's ability to adapt and reorganise itself [34].
Age-Related Changes	Spindle density declines with age, reflecting natural ageing or early signs of cognitive decline (e.g., Mild Cognitive Impairment, Alzheimer's Disease) [35].
Diagnosis and Monitoring of Neurological Disorders.	
Schizophrenia	Reduced spindle density and coherence [11].
Depression	Altered spindle patterns; disrupted sleep architecture [36].
PTSD	Faster spindle frequency; altered density linked to emotional dysregulation [37].
Insomnia	Fragmented, reduced spindle activity [38].
Neurodegenerative Disorders (Alzheimer's, Parkinson's)	Decreased spindle activity correlates with cognitive deficits.
Clinical and Research Applications.	
Polysomnography	Used to assess sleep quality and detect anomalies in clinical practice [39].
Neurofeedback and Therapy	Spindle modulation could become a therapeutic target, for example, via non-invasive brain stimulation [40].
Pharmacological Trials	Sleep spindle changes can serve as biomarkers for evaluating the effects of medications, such as sedatives and antidepressants [41].
Brain-Computer Interfaces (BCIs)	Real-time spindle detection could optimize cognitive enhancement technologies during sleep [42].

1) TRADITIONAL METHODS

Traditional detection methods depend on handcrafted characteristics extracted from frequency-domain, time-domain, and time-frequency domain analyses [43]. Frequency-domain-based methods influence spectral power within the sigma band to distinguish spindles from background activity. Time-domain-based detection methods use spindles' duration, amplitude, and root mean square (RMS) thresholds to categorize spindles. Furthermore, time-frequency domain-based methods, such as Teager Energy Operators (TEO) and wavelet transforms, offer enhanced resolution in detecting transient spindle oscillations. The discussed traditional methods, while effective, struggle with inter-individual variability and suffer from reliance on predefined parameters.

2) MACHINE LEARNING-BASED METHODS

ML-based methods enhance traditional sleep spindle detection by automatically learning discriminative features from the electroencephalogram (EEG) signal. Random Forests (RF), Support Vector Machines (SVM), and k-nearest Neighbors (k-NN) have been implemented to detect sleep spindles using features extracted from multichannel EEG recordings [44]. ML-based methods improve classification accuracy but do not generalize well to different datasets and require manual feature engineering.

3) DEEP LEARNING-BASED METHODS

Deep learning (DL)-based methods, particularly Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), have proved to perform exceptionally well in spindle detection. The U-Net framework has been exceptionally efficient, utilizing encoder-decoder structures to enhance spindle segmentation accuracy. CNNs extract hierarchical features directly from raw EEG signals to reduce the need for extensive feature engineering [45]. Hybrid RNN-CNN models and attention-based transformers further enhance temporal modeling, improving spindle classification [46]. Furthermore, Multiple Instance Learning (MIL)-based CNN models address label uncertainty by treating EEG signal segments as bags of instances, improving detection in weakly labeled datasets.

This survey highlights the progress in spindle detection by systematically comparing these methods and identifying future research directions for developing robust, generalizable, and interpretable AI-driven sleep analysis systems.

C. CHALLENGES IN DETECTING SLEEP SPINDLES AND PURPOSE OF THE SURVEY

Regardless of their waveform characteristics and apparent frequency, sleep spindles exhibit significant intersubject variability in duration, amplitude, and density, which complicates their automatic detection. Furthermore, spindles frequently intersect with other EEG oscillations, such as alpha waves and K-complexes, leading to possible misclassification. Traditional techniques to detect the spindle depend on manually identified thresholds, which can fail to generalize across varied EEG datasets and recording conditions [47]. Additionally, EEG datasets labeled by experts show rational inter-rater agreement (Cohen's kappa = 0.52), representing the subjective nature of manual spindle annotations [48]. In [49], authors determined the heritability of various sleep spindle characteristics using a twin study framework (40 DZ and 58 MZ twin pairs) and compared eight automated spindle detection algorithms to evaluate consistency in detecting spindle features such as duration, density, frequency and amplitude.

Considering the above-discussed challenges, there is a requirement for generalizable, robust, and interpretable frameworks for the detection of sleep spindles in EEG datasets. The proposed research survey aims to overcome the gap between traditional and modern spindle detection techniques, presenting a comparative evaluation of conventional feature-based and emerging ML/DL-based techniques. The survey also discussed their strengths, limitations, methodological foundations, and potential for clinical integration. By integrating findings from the latest advancements, this research contributes to developing a more robust, scalable, and accurate spindle detection framework for research and clinical applications.

D. RESEARCH MOTIVATION

Existing research reviews have examined automated spindle detection methods, but most have been limited in scope. For instance, current surveys mainly focus on traditional signal processing techniques or ML models, often lacking a systematic approach or quantitative analysis. More recent reviews have started to include DL. Still, they tend to be mainly descriptive and do not fully incorporate benchmark datasets, performance metrics, or comparative evaluations across different methodological groups. This research gap underscores the need for a comprehensive and systematic review that not only summarises past methods (traditional, ML and DL) but also critically assesses their strengths, limitations, and potential for real-world application.

E. RESEARCH AIM AND CONTRIBUTIONS

This survey aims to systematically review, compare, and synthesize current automated spindle detection approaches, highlight challenges, and recommend future directions. The proposed survey will provide a valuable reference for researchers, clinicians, and developers in the sleep science and neurotechnology communities. The following are the research contributions:

- We systematically identify and classify state-of-the-art methodologies used for automated sleep spindle detection, including traditional signal processing, machine learning, and deep learning.
- In the survey we evaluated and compared peer-reviewed papers published between 2010 and 2024, based on standardized set of performance metrics (Recall, F1-score, Accuracy, Sensitivity, Specificity, FPR, FNR).
- We performed a state-of-the-art literature review and comparative analysis using public EEG datasets such as DREAMS, MASS, and Sleep-EDF, which are readily available and widely used in the domain.
- To address the critical need for robust and interpretable sleep spindle detection systems in clinical diagnostics and neuroscience research, with a focus on real-world implementation the research survey identified the current challenges and formulated future research directions.

F. RESEARCH QUESTIONS

The following key research questions guide the survey:

RQ1: What are the most commonly used traditional, machine learning, and deep learning approaches used for the detection of automated sleep spindles in EEG recordings?

RQ2: How do the identified detection approaches compare in terms of computational efficiency, accuracy, generalizability, and interpretability?

RQ3: What state-of-the-art evaluation metrics and EEG datasets are used to assess spindle detection algorithms?

RQ4: What are the current limitations and open challenges in automated sleep spindle detection?

RQ5: What are the promising future directions to improve the scalability, reliability, and clinical applicability of spindle detection methods?

G. RESEARCH METHODOLOGY

This section presents the systematic approach to identifying, selecting, and analysing state-of-the-art sleep spindle detection techniques. The methodology follows a structured literature review strategy with well-defined inclusion and exclusion criteria, a targeted keyword search plan, and a multi-step paper selection process. The approach aims to ensure comprehensiveness, relevance, and scientific rigor.

1) INCLUSION AND EXCLUSION CRITERIA

In the survey, we included research papers published between 2015 and 2024 in reputable scientific journals or peer-reviewed conference proceedings, reported at least one standard evaluation metric such as accuracy, precision, recall, F1-score, specificity, sensitivity, or AUC, focused on signal processing, ML, or DL-based methodologies, focused on automatic sleep spindle detection in EEG signals, used standard benchmark EEG datasets, such as MASS, DREAMS, or Sleep-EDF and studies reported inter-rater reliability with Cohen's K greater then or equal to 0.75, ensuring consistency across annotated datasets. Where K was not explicitly available, studies were excluded under our criteria. Research studies were excluded which are non-English publications or non-peer-reviewed content (e.g., theses, technical reports), focused solely on sleep staging or other EEG events (e.g., K-complexes) without addressing spindle detection, studies using proprietary or inaccessible datasets that prevent reproducibility and papers lacking methodological clarity or evaluation on standard datasets.

2) KEYWORD SEARCH STRATEGY

A comprehensive systematic search was conducted using academic databases such as SpringerLink, ScienceDirect, IEEE Xplore, PubMed, and Google Scholar. To ensure comprehensiveness, Boolean operators and specific keyword combinations were used. The search strings were adjusted for each database to improve the relevance and coverage of the results. The following are the search criteria:

- "Signal processing" AND "spindle event detection"
- "Automatic spindle detection" OR "automated detection of sleep spindles"
- "Sleep spindle detection" AND "EEG"
- "Sleep EEG" AND "machine learning"
- "Spindle detection using deep learning"

3) RESEARCH PAPER SELECTION PROCESS

The selection of studies followed a multi-step process designed to screen and refine the corpus of literature systematically. Figure 2 represents the PRISMA flow diagram of the survey.

H. PAPER STRUCTURE

The proposed research survey is structured to provide a thorough and progressive understanding of automated sleep spindle detection. Section I introduced the biological and neurological importance of sleep spindles, their clinical relevance, and the motivation behind developing automated detection systems. Section II summarises existing literature reviews and surveys in the domain, highlighting their scope, methodologies, and contributions, and compares the current study in relation to previous work. Section III explores the physiological mechanisms, types, EEG characteristics, and cognitive roles of sleep spindles, including their relevance to neurological and psychiatric conditions. Section V categorizes and details the technical approaches into traditional signal processing, classical machine learning, and deep learning-based methods. Section VI presents a strengths–weaknesses–feasibility assessment of each approach, offering implementation notes and outlining clinical applicability challenges. Section IV discusses standardized performance metrics (e.g., accuracy, recall, F1-score) and highlights benchmark datasets such as MASS, DREAMS, and Sleep-EDF. Section VII comprehensively discussed the survey paper from the perspectives of interpretability, generalizability and clinical implementation. Section VIII identifies key challenges such as dataset limitations, label inconsistencies, lack of interpretability in DL models, and the difficulty of generalization across subjects, whereas Section IX proposes future research opportunities, including personalized models, explainable AI, real-time deployment, few-shot learning, and domain adaptation. Section X concludes the paper by summarising the key findings, reflecting on their implications for clinical and research domains, and outlining the next steps for implementing ML-based solutions on benchmark datasets. Table 2 highlights the proposed survey paper's major sections and key points, and Figure 3 highlights the structure of the survey paper.

II. SURVEYS ON SLEEP SPINDLES

In [26], the authors present a systematic review of DL techniques (2013–2020). The paper reviews 36 key studies that applied deep learning to classify sleep stages using overnight PSG (polysomnographic) recordings. It organises models by the DL architecture (CNN, RNN/LSTM, hybrid, autoencoders) and datasets used. Provides a comprehensive benchmark of performance metrics (accuracy) across models and datasets, including Sleep-EDF, MASS, SHHS, and

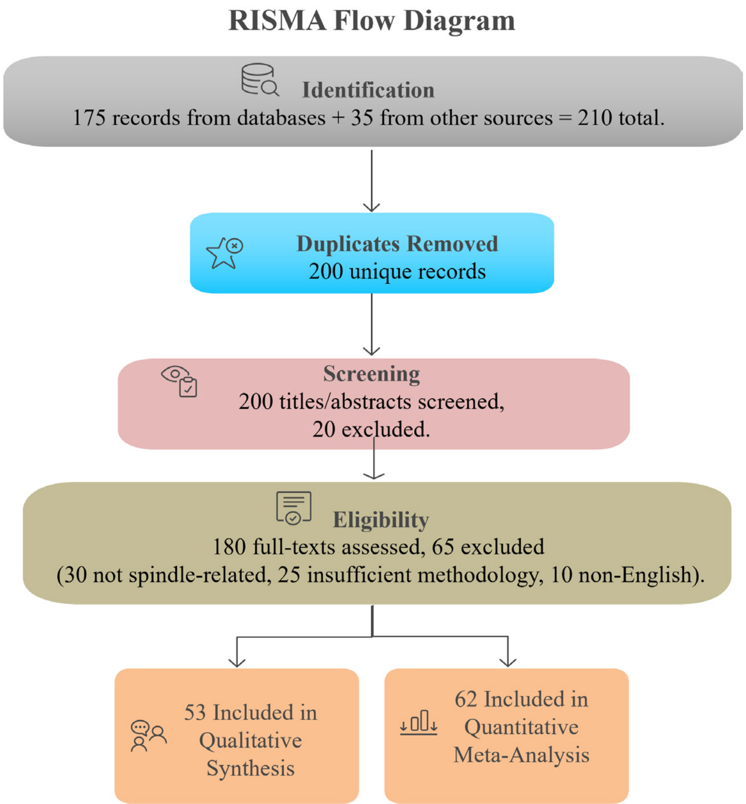

FIGURE 2. PRISMA Flow Diagram.

TABLE 2. Survey Major Sections and Key Points.

Section	Highlights
Introduction	Defines sleep spindles, importance, challenges, overview of evolution.
Related Surveys	Positions this survey against others (e.g., DL reviews, sleep staging).
Biological Background	Physiology of sleep spindles, EEG features, cognitive relevance.
Detection Techniques	Categorized into Traditional, ML-based, and DL-based approaches.
Challenges	Inter-rater variability, dataset scarcity, label noise, generalization issues.
Future Directions	Personalized models, XAI, few-shot learning, domain adaptation, edge computing.
Evaluation Metrics & Datasets	Metrics: Precision, Recall, F1, Specificity, FPR, FNR. Datasets: MASS, DREAMS, Sleep-EDF, CAPSLPDB.
Comparative Analysis	Strengths and weaknesses of Traditional, ML, DL approaches.
Conclusion	DL leads performance-wise, but lacks interpretability; future work needed for clinically trusted systems.

ISRUC. They also suggest a cloud-based sleep stage classification system using EEG signals as future work. In [50], the authors review 114 studies from 95 articles published between 2010 and 2021, following PRISMA methodology, and covered eight sleep disorders. They traced the evolution from ML to DL in sleep disorder detection and provided a broader scope than prior reviews (e.g., focused only on apnea or insomnia).

In [51], the authors conducted a PRISMA-based systematic review (2016–2019) on automated sleep stage classification (ASSC) using deep learning (DL). They reviewed 14 major DL-based studies, all using raw PSG signals or spectrograms for multi-class sleep stage classification. In [52], authors review traditional, ML, and DL methods for automated sleep spindle detection and classify state-of-the-art works published between 2010 and 2024 using performance metrics such as accuracy, F1-score, precision, recall, specificity, and sensitivity. They discussed the biological generation (e.g., thalamocortical loop), classification (slow vs fast spindles), and topographic EEG characteristics. Unlike previous literature that broadly examined EEG activity or sleep oscillations, [1] uniquely focuses on sleep spindle oscillations in adults diagnosed with sleep disorders. It includes 37 studies across insomnia, hypersomnia, and sleep-related movement disorders (like parasomnias). In [10], the authors focus on the alterations of sleep spindle characteristics in Alzheimer's disease (AD) and AD-related dementia rather than general sleep disturbances. Table 3 represents a comprehensive comparison of the proposed survey with the existing surveys and reviews.

III. SLEEP SPINDLES: BIOLOGICAL AND NEUROLOGICAL BACKGROUND

Sleep spindles are transient oscillatory events in the sigma band (11–16 Hz, usually 12–14 Hz) lasting at least 0.5 seconds, produced by thalamocortical circuits and most

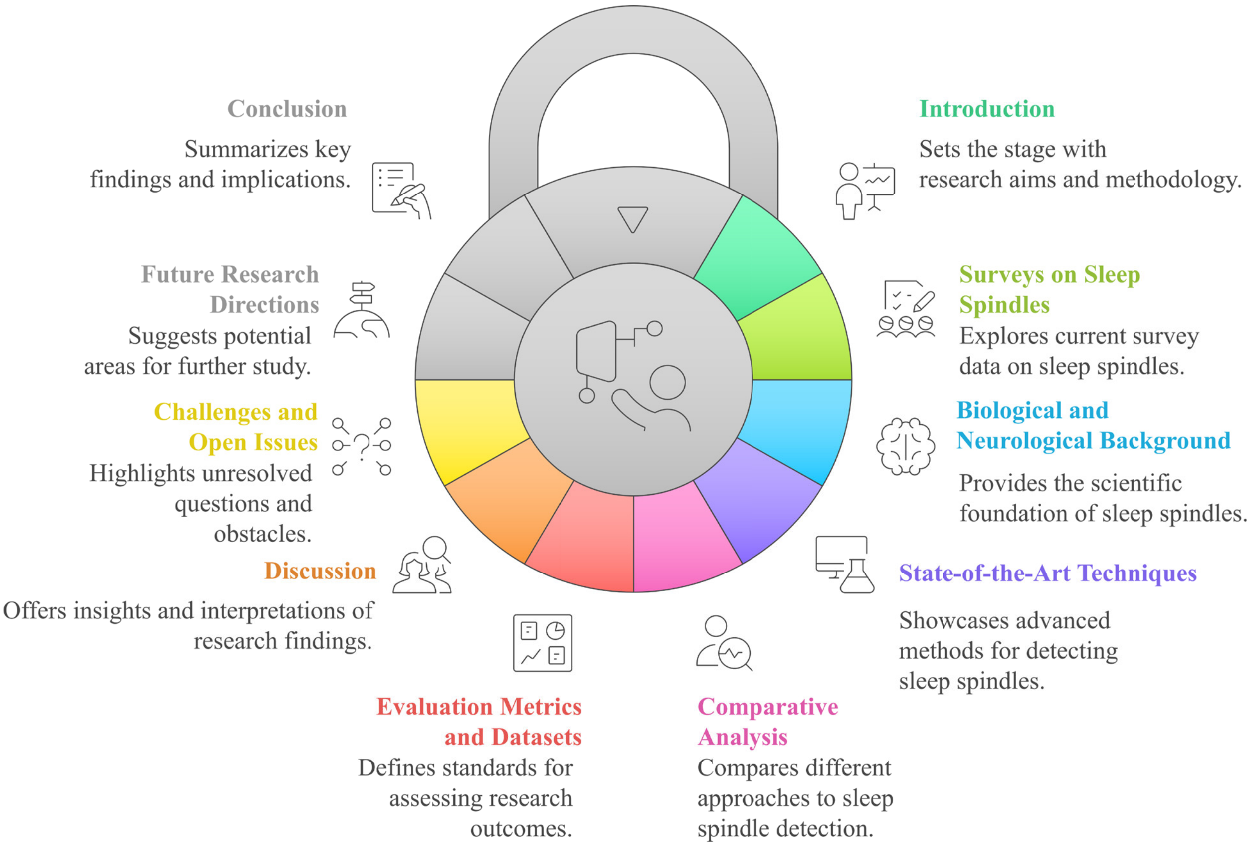

FIGURE 3. Survey Paper Flow Diagram.

TABLE 3. Comparison of the Proposed Survey with the Existing Surveys and Reviews.

Characteristics	Our Survey	[26]	[50]	[52]	[51]	[53]	[54]
Comparison with existing work	✓		✓				
Medical Background	✓	✓	✓	✓	✓	✓	✓
Traditional approaches	✓			✓		✓	
ML-based approaches	✓		✓	✓		✓	✓
DL-based approaches	✓	✓	✓	✓	✓		
Comparative analysis	✓						
Evaluation Metrics	✓	✓		✓	✓	✓	✓
Benchmark datasets	✓	✓	✓	✓	✓	✓	✓
Current challenges	✓						
Future directions	✓	✓	✓		✓		✓

prominent in central EEG leads examples [55]. Spindles are most prominent in the central area of the brain and are often observed through EEG recordings on channels like C3 and C4. They are regarded as biomarkers of healthy sleep physiology and are closely linked to processes such as neuroplasticity, memory consolidation, and cognitive performance. Abnormalities in spindles have been linked to neurological and psychiatric conditions, including schizophrenia, epilepsy, and neurodegenerative diseases (see Tables 1 for an outline of their functional roles and clinical associations). There are two types of sleep spindles: slow spindles and fast spindles [56].

- **Slow spindles (11–13 Hz),** usually dominant in the frontal brain regions.
- **Fast spindles (13–16 Hz),** typically found in the centro-parietal regions.

Sleep experts traditionally perform manual spindle detection according to guidelines from the AASM [3]. However, due to inter-rater variability, automatic detection systems using time-frequency analysis (e.g., Hilbert envelope, wavelet transform) and machine learning models are being increasingly employed to ensure consistent and objective identification [39]. In EEG analysis, sleep spindles are identified based on specific time, frequency, and morphological features [57]:

- **Amplitude:** Often exceeds 12–15 microvolts.
- **Frequency:** Spindles typically occur in the 11–16 Hz range. Slow and fast spindles are distinguished within this band.
- **Topography:** Most commonly detected in central and parietal EEG leads.

- **Waveform shape:** Characterized by a waxing and waning amplitude pattern.
- **Duration:** A valid spindle lasts between 0.5 and 2 seconds.

For automated detection, the biological characteristics of spindles are essential. Their unique morphology and spectral features underpin traditional thresholding methods; however, variability between individuals and the effects of sleep stage, age, and pathology necessitate more adaptable, data-driven algorithms. Therefore, understanding spindle physiology not only places them within the wider context of sleep research but also underscores the need for developing robust automated detection techniques that can consistently identify these clinically significant events. These factors directly influence the methodological approaches discussed in the following sections.

IV. EVALUATION METRICS AND BENCHMARK DATASETS

A range of evaluation metrics and benchmark datasets are commonly employed to assess the performance of sleep spindle detection algorithms. These evaluation metrics provide quantitative insight into classification accuracy, sensitivity, and error rates, while datasets ensure reproducibility and standardization across studies.

A. STANDARD EVALUATION METRICS

Evaluation metrics are crucial for quantifying the performance of detection systems. In sleep spindle detection, standard metrics include Precision, Accuracy, F1-score, Recall, False Positive Rate (FPR), and False Negative Rate (FNR).

1) PRECISION, ACCURACY, F1-SCORE, RECALL

Let TP, FP, TN, and FN represent True Positives, False Positives, True Negatives, and False Negatives, respectively. The most frequently used metrics are defined as follows:

- **Precision** (Positive Predictive Value) indicates how many of the predicted spindles were correct:

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Accuracy** measures the proportion of correct predictions:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **F1-score** is the harmonic mean of Precision and Recall:

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

- **Recall** (Sensitivity or True Positive Rate) measures the proportion of actual spindles correctly detected:

$$\text{Recall} = \frac{TP}{TP + FN}$$

These metrics are widely used to evaluate binary classifiers and detection-based models in spindle research.

2) FALSE POSITIVE RATE (FPR) AND FALSE NEGATIVE RATE (FNR)

Additional error-focused evaluation metrics include:

- **False Positive Rate (FPR)** measures the proportion of non-spindles incorrectly classified as spindles:

$$\text{FPR} = \frac{FP}{FP + TN}$$

- **False Negative Rate (FNR)** measures the proportion of missed spindle events:

$$\text{FNR} = \frac{FN}{FN + TP}$$

These error rates are significant in clinical applications where false alarms or missed detections may impact diagnosis or treatment decisions.

B. COMMONLY USED EEG DATASETS

Benchmark datasets are critical in enabling fair comparisons across spindle detection algorithms. They offer standardized EEG recordings, expert annotations, and consistent evaluation protocols.

1) SLEEP-EDF AND MASS (MONTREAL ARCHIVE OF SLEEP STUDIES)

Sleep-EDF (Sleep European Data Format) is popular dataset released by PhysioNet [58]. It includes whole-night EEG polysomnography recordings, primarily annotated for sleep stages and occasionally used for spindle detection. EEG channels typically include Fpz-Cz and Pz-Oz, with sampling rates of 100 or 200 Hz. Although primarily designed for sleep staging, its accessibility and data quality have led to its use in spindle-related studies.

MASS (Montreal Archive of Sleep Studies) is another comprehensive EEG dataset, comprising multiple subsets (SS1–SS5) with recordings from over 200 subjects [59]. The SS2 subset is widely used for spindle detection due to its high-quality annotations by multiple expert scorers. EEG signals are recorded at 256 Hz from central derivations (C3, C4, Cz) and follow the AASM scoring standard.

2) OTHER CLINICAL OR PUBLICLY AVAILABLE DATASETS

Several other datasets have contributed to the advancement of spindle detection methods:

- **CAPSLPDB** — A database for studying Cyclic Alternating Pattern (CAP) sleep events, including annotations for multiple EEG micro-events, including spindles, K-complexes, and arousal [60].
- **DREAMS** — A curated dataset for evaluating spindle detection algorithms, containing manually scored segments from 20 subjects with expert consensus annotations [61].
- **NSRR (National Sleep Research Resource)** — A repository that aggregates multiple annotated sleep study datasets, such as SHHS and MrOS, and sup-

ports large-scale validation of automated scoring algorithms [62].

- **Wisconsin Sleep Cohort (WSC)** — Offers a large and demographically diverse population with overnight PSG data, used in some recent studies for validating deep learning-based spindle detectors [63].

Using these datasets and unified evaluation metrics ensures reproducibility and facilitates benchmarking across traditional, machine learning, and deep learning approaches.

V. STATE-OF-THE-ART SLEEP SPINDLES DETECTION TECHNIQUES

Sleep spindle detection has evolved substantially from manual detection to advanced computational models. This section categorises the state-of-the-art approaches into three primary paradigms: traditional signal processing-based, classical machine learning-based, and modern deep learning-based approaches. Each category reflects a distinct methodological evolution in terms of feature extraction, classification precision, scalability, and adaptability to various EEG datasets. The goal is to systematically analyze these approaches, highlighting their working principles, strengths, limitations, and performance metrics to guide future research and practical deployment in clinical environments.

A. OVERVIEW—SYNTHESIS OF TRENDS

Three consistent trends emerge from the research papers reviewed in Tables 4, 5, and 6. First, the field has shifted from traditional thresholding and time–frequency methods to data-driven learning, with DL making its latest contribution and achieving the highest benchmark scores on MASS and DREAMS datasets. Second, the choice of dataset significantly influences performance: results trained and evaluated on MASS generally outperform those on DREAMS or mixed clinical sets, emphasising the importance of annotation density, channel montage, and sampling rate. Third, although DL models often achieve the top F1 scores, ML methods remain competitive and are often more practical in small-data or resource-limited settings. Traditional signal-based approaches continue to provide low-latency, interpretable baselines suitable for embedded or bedside applications. These patterns underpin the comparative guidance in Section VI and the deployment considerations (real-time, interpretability, generalisability) discussed later.

B. TRADITIONAL SIGNAL PROCESSING-BASED APPROACHES

The traditional signal processing-based sleep spindle detection approach primarily relies on handcrafted signal processing techniques, which are divided into frequency, time, and time-frequency domain analyses. These techniques examine the features of sleep spindles, including duration, amplitude, and spectral content, by applying fixed or adaptive thresholds to isolate spindle events. While these techniques have laid the foundation for automated detection, they often struggle with noise sensitivity, inter-individual variability, and lack of generalizability across datasets. Nevertheless, they are valuable due to their low computational complexity and interoperability.

1) TIME-DOMAIN METHODS

In [64], the authors benchmark four automatic spindle detectors (RMS, Sigma Index, Relative Spindle Power, and Teager Energy Operator) using an acceptable temporal resolution and multiple databases, including both open-access and closed-access ones. The study also critiques the reliability of expert annotations and promotes open science tools, such as the Spyndle Python package. To measure the framework's performance, the authors used sensitivity, precision (PPV), F1-score, Cohen's kappa, Matthews correlation coefficient (MCC), and ROC and PR curves and emphasised threshold-dependent evaluation rather than fixed thresholds. The authors used four datasets: DDB (DREAMS Database), MASS (Montreal Archive of Sleep Studies), NDB (Nightmare Study Dataset), and SDB (Sleep Density Dataset), focusing on stage N2 sleep [64]. A nonlinear time-domain method for sleep spindle detection is introduced by [65] using the Delay Differential Analysis (DDA) approach. The proposed method operates on raw EEG without filtering or feature engineering. Performs comparably to spectral methods but is computationally lighter and captures dynamical features beyond spectral signatures [65].

In [66], the author proposes a novel, automated sleep spindle detection algorithm based on bivariate normal modelling of spindle amplitude and frequency distributions. Instead of using fixed amplitude and frequency thresholds, it adapts dynamically to individual EEG derivations [66]. This paper [67] provides the first dedicated review linking sleep spindle dynamics to PTSD, covering both mechanistic underpinnings and clinical findings. The authors review experimental and clinical studies focused on spindle density, amplitude, frequency, morphology, and nesting in individuals with PTSD.

2) FREQUENCY-DOMAIN METHODS

In [68], the author aimed to develop an efficient, simple, and explainable sleep spindle detection algorithm (A7) that emulates human scoring by utilising signal characteristics derived from sigma-filtered data and raw EEG, with a focus on mimicking human interpretability and minimising false positives. The authors used the WSC110sub dataset (Wisconsin Sleep Cohort, comprising 110 healthy middle-aged subjects and 13 hours of N2 sleep) for the experiments and evaluated performance using precision, recall, and F1-score of 0.74, 0.68, and 0.70, respectively. Authors in [69] compared two well-established automatic sleep spindle detection methods 1) fixed frequency (FixF): Uses pre-defined frequency bands (11–13 Hz for slow, 13–15 Hz for fast spindles) and 2) Individual Adjustment Method (IAM): Adapts frequency and amplitude criteria to each subject. The authors used a dataset of 161 healthy volunteers (17–69 years old) and argued for using individualized frequency ranges, especially when studying cognitive correlates. In [70], authors compared the effectiveness of four Power Spectral Density (PSD) methods, including FFT, Welch, AR, and MUSIC, for automatic sleep spindle detection. They used a custom dataset comprising 5 subjects, with EEG recorded at 128 Hz, and evaluated the selected methods using accuracy.

3) TIME-FREQUENCY ANALYSIS

Using the teager energy operator (TEO) and spectral edge frequency (SEF), [71], design and validate a low-power ASIC system-on-chip (SoC) for automatic sleep spindle detection. The aim is to achieve ultralow power consumption for real-time, wearable EEG applications without compromising detection accuracy. The authors utilised the DREAMS Sleep Spindles dataset, employing sensitivity and specificity as evaluation metrics. The authors in [72] developed an enhanced sleep spindle detection algorithm using Synchrosqueezing Transform (SST) approach that extracts oscillatory EEG components (11–16 Hz) and mimics expert visual scoring by comparing spindle-like events to the surrounding background. The authors used a dataset of 2 healthy adult subjects, a 24-year-old male and a 30-year-old female. They used sensitivity, specificity, selectivity, and detection correlation Coefficient as evaluation metrics and achieved 98.1% specificity.

4) EMPIRICAL MODE DECOMPOSITION (EMD)

The aim of the authors [73] was to develop and validate a CWT-based spindle detection algorithm that: accounts for inter-individual variability in spindle frequency and EEG amplitude, separates slow vs. fast spindles adaptively, compares results with both human scoring and the SIESTA commercial detector, and applies the method to memory consolidation and heritability analysis using twin data. The authors employed the continuous wavelet transform (CWT) using the Morlet wavelet approach within the developed framework, utilising 18 nap recordings from 10 healthy participants. In [48], using complex demodulation (CD) and Z-score normalisation, the authors validated a novel individualised sleep spindle detection method. Authors used complex demodulation to extract the instantaneous sigma-band power (13.5 Hz, 11–16 Hz range) and Z-score normalization using a 60s moving window per channel (compensates for inter-/intra-individual variability). For the experiments, [48] used MASS SS2 (Montreal Archive of Sleep Studies) dataset and precision, recall, f1-score and phi coefficient as evaluation metrics. In [74], the authors propose a stage-independent and single-channel sleep spindle detection algorithm that utilises the CWT with a Morlet basis and implements probabilistic detection with local smoothing, comparing it against six popular algorithms on public datasets (DREAMS, MASS). The authors used sensitivity, specificity, false discovery rate and weighted kappa as evaluation metrics. In [75], the authors present the development and comparative evaluation of four automated methods for detecting bilateral sleep spindles in EEG recordings: a combination detector (a new method), a fuzzy detector (previously developed), a bilateral sigma index, and a fixed amplitude detector. This paper [76] addresses a long-standing issue in sleep spindle research: the lack of standardization in evaluating and comparing automatic detection algorithms. The authors propose a unified assessment framework that defines consistent evaluation metrics and applies it to their detection algorithm.

In [77], the authors develop and validate a real-time automated sleep spindle detection system. The developed system works on single and multiple EEG channels. The authors used precision, sensitivity, and f1-score as evaluation metrics and selected Nap EEG (N = 20) and Full-night Sleep EEG (N = 10) datasets for the experiments. In [78], the authors propose and validate a sliding window-based probability estimation (SWPE) method and its enhanced version, SWPE-E, for spindle detection. The authors used continuous wavelet transform, sliding window-based estimation (SWPE), and envelope enhancement (SWPE-E) approaches. They used precision, F1-score, accuracy, sensitivity, FDR, and the DREAMS Sleep Spindle Dataset for framework evaluation as benchmarks. To separate EEG into transient and oscillatory components using sparse low-rank decomposition, authors in [79] propose a novel multichannel sleep spindle detection algorithm (McSleep) using the TEO, which enables global and local spindle detection across multiple EEG channels. For the experiments, the authors chose the DREAMS AND MASS SSE datasets, and for evaluation, they selected the F1 score, MCC, recall, and precision.

a: KEY TAKEAWAYS

Table 4 represents a cumulative summary of traditional techniques used for sleep spindle detection. Traditional signal-based approaches primarily rely on amplitude, frequency, and duration thresholds, with notable differences observed across time–frequency transforms, such as wavelet and Fourier analyses. While these methods are computationally efficient and fairly easy to interpret, their effectiveness can be affected by noise and variability between subjects. Overall, they remain useful as baseline techniques and for real-time low-resource situations but are increasingly surpassed by machine learning and deep learning methods in large-scale assessments.

C. MACHINE LEARNING-BASED APPROACHES

Machine learning-based approaches have introduced a shift in sleep spindle detection by enabling adaptive decision-making and data-driven feature learning. These models typically operate on manually extracted features extracted from EEG signals, including statistical moments, spectral power, and time-frequency coefficients. ML models such as Random Forests (RF), Support Vector Machines (SVM), and k-Nearest Neighbors (k-NN) are utilized for classification,

TABLE 4. Summary of traditional techniques for sleep spindles detection.

Ref.	Objectives	Dataset	Approach	Evaluation Metrics
[78]	Propose and validate a sliding window-based probability estimation (SWPE) method and its enhanced version SWPE-E for spindle detection.	DREAMS Sleep Spindle Database	SWPE, and SWPE-E	Precision, F1-score, Accuracy, Sensitivity, and FDR
[71]	Design and validate a low-power ASIC system-on-chip for automatic sleep spindle detection.	DREAMS	EEG Filtering, TEO Block, Duration Filtering, SEF50 Block, and Decision Logic	Sensitivity and Specificity
[77]	Develop and validate a real-time, automated sleep spindle detection system (RTSD).	Nap EEG and Full-night Sleep EEG	Real-Time Spindle Detector (RTSD)	Precision, Sensitivity, F1-score
[74]	Proposed a stage-independent and single-channel sleep spindle detection algorithm that uses the Continuous Wavelet Transform (CWT) with Morlet basis.	DREAMS, MASS	Continuous Wavelet Transform	Sensitivity, Specificity, False Discovery Rate, and Weighted Kappa
[48]	Validated a novel individualised sleep spindle detection method using Complex Demodulation (CD) for signal extraction and Z-score normalisation via a 60s sliding window.	MASS SS2	Complex Demodulation and Z-score Normalization	Precision, Recall, F1-score, and Phi Coefficient
[68]	Develop an efficient, simple, and explainable sleep spindle detection algorithm that emulates human scoring by utilizing signal characteristics derived from sigma-filtered data and raw EEG.	Wisconsin Sleep Cohort Subset (WSC110sub)	A7 (signal processing-based, non-ML)	Precision, Recall, F1-score, Spindle Density Correlation with Experts: $R^2 = 0.82$
[73]	Developed and validated a CWT-based spindle detection algorithm that accounts for inter-individual variability in spindle frequency and EEG amplitude.	18 naps from 10 subjects	Continuous Wavelet Transform (CWT)	Kappa, Sensitivity, Specificity, and Precision
[64]	Benchmark four automatic spindle detectors (RMS, Sigma Index, Relative Spindle Power, and Teager Energy Operator) using fine temporal resolution and multiple datasets.	DREAMS, MASS, NDB, and SDB	RMS Amplitude Detector, Sigma Index Detector, Relative Spindle Power Detector, and TEO	Sensitivity, Precision (PPV), F1-score, Cohen's Kappa, Matthews Correlation Coefficient (MCC), ROC and PR curves

offering enhanced accuracy and robustness compared to traditional methods. However, their performance depends on careful feature engineering and may require balanced, well-annotated datasets.

1) CLASSICAL MACHINE LEARNING MODELS

Using SVM-based multivariate classification, cross-feature selection and normalization [80] develop and validate a robust, single-channel, automatic sleep spindle detector (MUSSDET). Using evaluation metrics such as accuracy, sensitivity, specificity, precision, F1 score, and MCC, the authors conclude that the performance is consistently better on MASS than on DREAMS due to differences in data clarity and sampling rates using the SVM model. A novel algorithm for automatic sleep spindle detection is proposed by [81] using an SVM classifier to determine spindle likelihood, Wavelet Transform (WT) for spectral feature extraction and Gaussian-based smoothing for noise robustness. The proposed algorithm is evaluated on a public dataset (DREAMS) using well-structured comparisons and robust metrics. The proposed method performed best in specificity (92.8%), with a well-balanced F1-score despite slightly lower sensitivity than Tsanas' method.

A Random Forest-based method (Spindle-AI) framework is proposed by [82] to detect both the number and duration of sleep spindles in infant EEG, and the system works on single-channel EEG (F4-C4, F3-C3). The authors implemented the model on a 141-EEG recording dataset from 4-month-old ex-term infants and achieved 93.3% sensitivity. A Random Forest-based supervised classifier is proposed by [83] that automatically detects infant sleep spindles. The proposed framework focused on identifying both spindle presence and duration and was designed for large-scale infant EEG (N = 141 ex-term + 6 ex-preterm). They applied SMOTE (Synthetic Minority Over-sampling Technique) to balance the dataset, as the duration of spindles was significantly shorter than that of non-spindle intervals. The authors utilised an EEG dataset comprising 147 infants, employing accuracy, sensitivity, specificity, and MCC as evaluation metrics, and achieved 94.8% accuracy on the test dataset. The authors evaluated a Random Forest (RF)-based supervised classifier for automatic sleep spindle detection using features from EEG data filtered in multiple frequency bands [49]. The aim was to outperform or avoid the overfitting issues common with ANN and SVM classifiers, focusing on low-complexity, real-time-capable features. The authors used the MASS SS2 dataset, used a random forest classifier (10 trees, 2 features/node) and achieved specificity 96.73%

In [84], the authors explore how combining linear (time-series) and nonlinear (chaotic) EEG features enhances automatic sleep spindle detection and spindle prediction (several seconds in advance). The author mainly focused on how chaotic feature-scattering intensity maps can help define decision boundaries more clearly. The authors implemented Multi-Layer Perceptron (MLP) and k-Nearest Neighbors (KNN) classifiers and used accuracy, sensitivity and specificity as evaluation metrics. Based on the results, MLP outperforms KNN across all feature configurations. Using Gaussian Mixture Models (GMM) [85], they developed and evaluated an unsupervised clustering-based sleep spindle detection method. Authors used the sigma ratio (RMS of spindle band (10.5–16 Hz) vs total signal) and sigma index (mean energy of spindle band / (Alpha + Beta energy)) as input features. The authors used two datasets for experiments: the MASS SS2 Cohort and the Berlin Sleep Lab. The authors used sensitivity, False Positive Rate, F1 Score and recall as evaluation metrics. In [86], authors systematically compare the performance of conventional ML and DL methods for automatic sleep stage classification (ASSC), particularly focusing on robustness to feature selection, accuracy, and the effect of reducing the number of channels (e.g., wearable EEG). The authors used the Sleep-EDF Expanded (PhysioNet) dataset and achieved 89.6% accuracy from the SVM model.

2) HYBRID APPROACHES

Authors in [87] develop a hierarchical fusion algorithm for automatic sleep spindle detection that enhances accuracy and efficiency and combines multiple detection methods (wavelet & RMS) and machine learning (k-means). The authors used a dataset of 20 patients with diagnosed sleep disorders, implemented morlet wavelet transform (signal processing), RMS detection (heuristics), and k-means clustering (ML), and used precision, recall, f1-score, accuracy and specificity as evaluation metrics. In [88], authors improve and robustly evaluate the performance of existing sleep spindle detectors using Multi-Objective Evolutionary Algorithms (MOEAs), optimization the performance of 9 different algorithms (6 base + 3 hybrid) using Pareto fronts to derive performance metrics like F1-score and Precision-Recall (PR) curves. For the experiments, the authors used DREAMS and MASS SS2 datasets.

In [89], authors developed and optimised a Filter-Based Thresholding (FBT) method for sleep spindle detection that provides automated labelling for training ML models and works across multichannel EEG. In the proposed research work, the authors used the CCNY Study as a primary dataset and the DREAMS dataset for external validation. SPINDILOMETER is a machine-learning-based diagnostic model integrated with polysomnography (PSG) systems introduced by [90]. It is designed to automatically detect and quantify sleep spindles in EEG signals, thereby achieving a reliable and fast diagnostic enhancement tool for PSG. The authors implemented several ML models, including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Trees (DT), Naive Bayes (NB), and Extra Trees Classifier (ETC). They achieved 94.61% accuracy from the KKN model.

In [91], the authors propose a novel hybrid method (SST-RUS) for automated sleep spindle detection that extracts features using Synchrosqueezed Wavelet Transform (SST), handles class imbalance using Random Under-Sampling Boosting (RUSBoost), and eliminates the need for threshold tuning common in template-matching methods. The authors employed RUSBoost, a combination of Random Under-Sampling and Boosting, utilising the MASS-C1 and DREAMS datasets for implementation. They selected sensitivity, F1-score, and PPV as performance evaluation metrics. In [92] authors proposed a parametric spindle detection framework Spindler that utilizes matching pursuit (MP) with Gabor atoms, avoids reliance on human-labeled training data, selects parameters based on the stability of spindle metrics (rate, duration, etc.), supports both unsupervised and supervised modes, and provides an open-source MATLAB toolbox for benchmarking various algorithms. Authors used the Spindler algorithm on two datasets, MASS SS2 (19 subjects, full-night NREM) and DREAMS Sleep Spindles (30-min excerpts, Cz channel) and calculated spindle surfaces: rate, length, time fraction. In [93], authors propose a hybrid spindle detection framework by combining wavelet-fourier analysis, statistical feature selection using Kruskal-Wallis and machine learning classifiers (LS-SVM, K-NN, K-means, C4.5) for final detection. The authors achieve 97.9% accuracy from the SVM classifier.

a: KEY TAKEAWAYS

Table 5 represents a cumulative summary of ML-based techniques used for sleep spindle detection. ML-based methods demonstrate a clear improvement over threshold-based techniques by utilising handcrafted features and statistical learning algorithms, such as SVMs, Random Forests, and k-NN. Their strength lies in moderate data requirements and adaptability to various recording conditions, balancing accuracy and computational efficiency. However, their reliance on expert-defined features limits scalability, and performance often stagnates without large, annotated datasets. These methods are therefore most effective in clinical contexts where dataset size and resources are limited.

D. DEEP LEARNING-BASED APPROACHES

Deep learning-based approaches represent the cutting edge of sleep spindle detection, leveraging the capacity of neural networks to learn complex, hierarchical representations directly from raw EEG data. DL models such as Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and hybrid CNN-RNN frameworks eliminate the need for handcrafted features, enabling end-to-end training. These models have proven superior generalization, especially on large, diverse datasets, and show promise in handling label noise, temporal dynamics, and spatial dependencies across channels. Despite their success, challenges remain in interpretability, computational demand, and the need for high-quality annotated data.

TABLE 5. Summary of ML-Based techniques for sleep spindles detection.

Ref.	Objective	Dataset	Approach	Evaluation Metric
[94]	To develop an interpretable spindle detector using sliding-window features and XGBoost with a new F1 score metric.	MASS SS2, COGNITION, DREAMS (combined total ∼11,000 subjects)	132 handcrafted features; Feature selection via boot-strapped XGBoost; classifier with 60 estimators.	F1-score: 80.5–84.7% (E2), outperforms DOSED, A7, SpindleU-Net.
[90]	Real-time detection system for PSG using statistical + ML models, evaluates spindle features across subjects.	72 subjects (clinical PSG), EEG: F3-M2, F4-M1, C3-M2, etc.	PSD, CWT, NGS, BGS features; classifiers: KNN, SVM, RF, NB, Extra Trees.	KNN Acc: 94.6%, MCC: 0.89, AUC: 0.95, F1: 94.3%.
[91]	Develop an RF-based spindle detection method using time-frequency features from synchrosqueezed wavelet transform.	MASS SS2	SSWT + RF classifier on extracted signal energy features.	Sensitivity: 87%, Specificity: 93%, F1-score: 84%.
[49]	Evaluate the Random Forest classifier with spectral feature ratios on the MASS SS2 dataset.	MASS SS2 (19 subjects), C3, Cz, C4 EEG channels	5 bandpass filters + 3 statistical ratios as features; RF classifier.	Sensitivity: 71.2%, Specificity: 96.7%, FDR: 47.4%.
[81]	Use SVM classification of wavelet-based EEG features for spindle detection.	DREAMS dataset	Mexican hat wavelet transforms, Gaussian smoothing, linear SVM.	Specificity: 96.3%, FDR: 46.3%, Sensitivity: 70.7%.
[82]	Quantify the number and duration of spindles in infant EEG using ML models.	Infant EEG (0–1 year), channel Cz	Preprocessing + rule-based event scoring + regression models.	RMSE for spindle count/duration estimation < 0.1.
[85]	Develop a spindle detection algorithm using multivariate GMM with adaptive features.	MASS SS2 (C3 EEG), manually labelled by experts	GMM clustering with spectral and statistical features, adapted per subject.	F1: 82%, Sensitivity: 85%, Specificity: 90%.
[92]	Test supervised classifiers using wavelet-transformed EEG features for spindle detection.	MASS subset, expert-labeled C3 signals	Wavelet + RMS + statistical moments + SVM, RF.	RF F1: 84.7%, SVM F1: 82.2%.
[94]	Create an interpretable spindle detection framework (SpinCo) with novel metrics for comparing with human annotations.	MASS SS2, COGNITION, DREAMS	XGBoost with sliding-window features; bootstrapped feature selection; novel F1* event metric.	F1*: 80.5–84.7%, outperforms DOSED, A7, SpindleU-Net in population-level validation.
[86]	Compare multiple classical ML models vs DL models for automatic sleep staging with reduced EEG channels.	Sleep-EDF Expanded (Fpz-Cz, Pz-Oz), 21,265 epochs	SVM, RF, k-NN, MLP, LSTM, Bi-LSTM with 62 handcrafted features.	Acc: 89.6% (SVM-RBF), MLP: 89%, LSTM: 87.9%, BiLSTM: 87.9%.
[74]	Benchmark classical ML models using CWT-transformed EEG features for spindle detection.	DREAMS, Cz EEG	CWT + statistical feature extraction + Logistic Regression, SVM.	Sensitivity: 90.7%, F1-score competitive with expert agreement.

1) CONVOLUTIONAL NEURAL NETWORKS (CNNS)

To design a data-efficient CNN-based model, named SUMO (Slim U-Net trained on MODA) [95], a framework was proposed that can accurately detect sleep spindles across age groups, surpassing both experts and state-of-the-art algorithms (A7), and derive reliable spindle-related biomarkers, such as density and duration. The authors utilised the MODA (Massive Online Data Annotation) dataset, a three-level U-Net-style convolutional neural network, and recall, precision, and F1-score as evaluation metrics. In [96], authors developed the first U-Net-based framework for point-wise sleep spindle detection and applied a 1D convolutional U-Net with an attention module for feature focusing. For the experiments, the authors selected the MASS and DREAM datasets and used precision, F1-score, and recall as evaluation metrics. The paper [97] proposes a deep VGG-like CNN architecture for automatic sleep stage classification and visualises the internal layers to understand emergent signal features in EEG and EOG, and achieved 81% overall accuracy on the Sleep-EDF Expanded dataset. The authors demonstrate that deep CNNs classify sleep stages with near-human accuracy and spontaneously learn human-relevant features like sleep spindles, slow waves, and rapid eye movements.

Propose real-time, smartphone-app-compatible methods for clinical adoption by [98] to revolutionize spindle detection by visually analyzing EEG waveform images—instead of EEG time-series signals—using state-of-the-art deep learning object detection models. The authors compared YOLOv4 and YOLOX architectures and enabled automated spindle location via bounding boxes. They used the MASS SS2 dataset and achieved 97.24% average precision on the Tiny Coco model. For sleep stage classification (Wake, NREM, REM), [60] developed a 1D-CNN-based deep learning model for Cyclic Alternating Pattern (CAP) detection, which includes phases with sleep spindles, especially in the A1 phase. The goal of the paper is to automate the detection of both macrostructure (sleep stages) and microstructure (CAP) and validate on high-sampling-rate (512 Hz) EEG from CAPSLPDB, and achieved 90.46% accuracy.

In [99], authors address the label noise problem in sleep spindle detection using a CNN-based Multiple Instance Learning (MIL) model with an iterative label refinement mechanism to tackle the high inter-expert and intra-expert variability in spindle annotations. The authors utilised the MASS and DREAMS datasets and achieved 95.38% accuracy on the MASS dataset. A CNN-based model for classifying sleep spindles and exploring the effectiveness of transfer learning in applying a model trained on healthy individuals to data from patients with insomnia is proposed by [100]. The research aimed to address the difficulty in manual spindle annotation for clinical populations and optimize classification performance with CNN feature learning and layer-specific transfer. A recall value of 94.53% on healthy and 94.17% on insomnia individuals is achieved. In [94], the authors developed a transparent, accurate, and interpretable spindle detection framework called SpinCo based on the XGBoost gradient-boosted tree model. The authors used three datasets: MASS SS2, DREAMS and COGNITION (private).

2) HYBRID DEEP LEARNING MODELS

Authors in [101] proposed a deep learning-based framework for the automated detection of both the duration and number of sleep spindles in infant EEG data, explicitly targeting ex-term and ex-preterm infants. The aim was to support physicians with a visual and interpretable system that mimics expert annotation without requiring domain-specific feature engineering. The authors implemented CNN and bidirectional LSTM on a recorded dataset consisting of 141 ex-term infants (81 for training, 30 for validation, and 30 for testing) and 54 ex-preterm infants used for independent testing. They used sensitivity: 91.9%–96.5%, specificity: 95.3%–96.7%, f1-score: 0.924%v–0.954%, and MCC 0.878%–0.922% as evaluation metrics. In [102], authors developed a generic and accurate sleep spindle detection framework that handles uncertain spindle durations via an elastic time-window mechanism. The proposed framework represents weak features by combining deep features (CNN) and macro-scale entropy-based features. The authors emphasise onset/offset accuracy and handling imbalanced datasets via focal loss. The authors utilised the DREAMS dataset (six excerpts, C3-A1/Cz-A1 channels, 50–200 Hz) for the experiments, employing f1-score (0.664 ± 0.11), precision (0.654 ± 0.13), and recall (0.687 ± 0.09) values as evaluation metrics.

To present SEED (Sleep EEG Event Detector), [103] proposed a deep learning model combining CNNS + BiLSTMs, which uses long context windows (20s) for precise temporal localisation and detects both sleep spindles (SS) and K-complexes (KC) using raw EEG. The researcher used MASS2 (E1, E2) and NSRR6 (6 sets) datasets and achieved an 80.8% F1-score on the SEED detector. In [104], authors develop a flexible, event-agnostic deep learning architecture called RED (Recurrent Event Detector) for automatic detection of sleep micro-events (specifically spindles and K-complexes) using time-frequency domain (CWT spectrogram) and time-domain EEG. For the experiments, the authors used the MASS S2 dataset and achieved an 81.2% value of the F1-score.

To evaluate the ability of Deep Belief Networks (DBNs), the authors [105] proposed a framework for sleep spindle detection by replacing the expert "gold standard" with a crowdsourced dataset and comparing DBNs against traditional classifiers. The authors used the F1-score to evaluate the results. To investigate the effectiveness of several neural network architectures—DNN, LSTM, CNN, and CNN-LSTM hybrids, [106] proposed automated sleep spindle detection using EEG data from the MASS SS2 database. The study also includes a value-based thresholding method as a baseline for comparison. The research achieved 67.15% accuracy from the CNN-LSTM (Torch) model. The authors in [107] proposed a two-stage (Stage 1 – Pre-detection and Stage 2 – Refinement) framework for sleep spindle detection and validated their method on two public datasets: MASS and DREAMS. The paper used both Sample-Based Evaluation (SBE) (ACC, SEN, SPE, and KAPPA) and Event-Based Evaluation (EBE) (RE, PR, F1, and Overlap criterion (20% overlap considered a match)). They achieved F1 = 0.814, Kappa = 0.694 on the MASS dataset (union of expert annotations), and F1 = 0.690, Kappa = 0.539 on the DREAMS dataset. The proposed method is robust, fast, and suitable for real-time applications, as it works with single-channel EEG (minimising subject discomfort). Adaptive thresholds overcome inter-subject variability and outperform or match the performance of state-of-the-art methods and experts.

The authors in [108] proposed a sleep spindle detection method based on Concentration of Frequency and Time (ConceFT), a nonlinear time-frequency (TF) analysis tool that combines Synchrosqueezing Transform (SST) and Multitapering (nonlinear adaptation). They used DREAMS and MASS datasets to validate the proposed method, reporting SEN, Precision, and F1 as evaluation metrics. The results were F1 scores of 0.678 (a7), 0.674 (SUMO), and 0.765 (Conceft-S) on the DREAMS dataset (with SEN=0.750 and PRE=0.792), and F1 scores of 0.692 (a7), 0.782 (SUMO), and 0.791 (Conceft-S) on the MASS dataset (with SEN=0.800 and PRE=0.801). ConceFT provides a robust, interpretable, and accurate method for spindle detection, which is either comparable to or better than state-of-the-art methods (A7, SUMO). The proposed method has only been tested on single-channel EEG during the N2 sleep stage and requires validation on larger datasets (e.g., MODA). To develop a general-purpose deep learning architecture for joint detection of micro-events in EEG (e.g., spindles and K-complexes), [109] proposed a framework that predicts event onset, duration, and label and does not rely on sleep stage annotations. The authors used the MASS SS2 dataset and precision, recall, and f1 score as evaluation metrics.

a: KEY TAKEAWAYS

Table 6 represents a cumulative summary of DL-based techniques used for sleep spindle detection. DL-based methods dominate recent research, with CNNs, RNNs, and

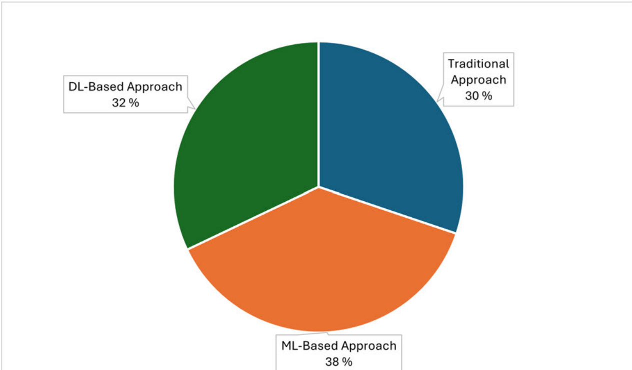

FIGURE 4. Study Counts by Methods (Traditional, ML and DL).

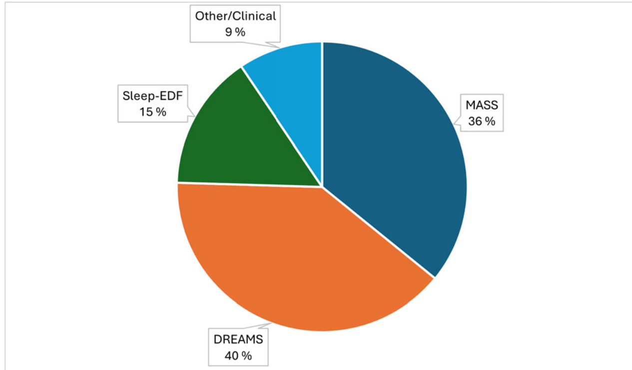

FIGURE 5. Dataset Usage Distribution Across Included Studies (stacked bars by MASS, DREAMS, Sleep-EDF, and "Other/Clinical".

hybrid models consistently outperforming traditional and machine learning approaches across benchmark datasets. Their capacity to learn features directly from raw EEG data and to generalise across noisy, diverse recordings underpins their superior performance. However, they demand substantial annotated data and computational resources, and their lack of interpretability remains a barrier to clinical application. The increasing emphasis on explainability and lightweight architectures underscores ongoing efforts to address this gap for real-world deployment.

Pie chart (Figure 4) illustrates the distribution of reviewed studies by methodological family in your survey of automated sleep spindle detection:

- **Traditional Approaches (30%)** still account for a significant portion, especially in earlier work. These methods persist in some contexts due to their computational simplicity, interpretability, and suitability for low-resource environments.
- **ML–Based Approaches (38%)** form the largest share. This shows that ML methods such as SVMs, Random Forests, and k-NN have been widely adopted, particularly in mid-2020s research, where feature engineering and moderate dataset requirements made them practical.
- **DL–Based Approaches (32%)** represent a rapidly growing segment. Even though DL emerged later, its strong performance on benchmark datasets has quickly positioned it as the dominant recent trend.

The pie chart (Figure 5) illustrates the dataset usage distribution across the studies included in the survey:

- **Sleep-EDF (15%)** appears less often, largely because it is more commonly applied in sleep staging research rather than spindle-specific detection.
- **MASS (36%)** is heavily utilised, especially in studies focused on large-scale validation, due to its extensive multi-subject recordings and reliable labelling.
- **DREAMS (40%)** is the most frequently used dataset, reflecting its accessibility, standardized annotations, and suitability for benchmarking detection algorithms.
- Other/Clinical datasets (9%) represent studies conducted on local hospital or lab data, which provide valuable diversity but are less standardized, limiting comparability across studies.

In summary, the evolution of sleep spindle detection approaches reflects a nonstop effort to improve generalizability, accuracy, and clinical relevance. Traditional approaches offer interpretability and simplicity, while machine learning (ML) models enhance adaptability through data-driven insights. DL approaches stand at the forefront, offering unprecedented performance but introducing new complexities related to explainability, training, and data dependency. As research advances, hybrid models and domain-adaptive frameworks may offer the most promising path forward, combining the interpretability of traditional methods with the learning power of modern AI systems.

VI. COMPARATIVE ANALYSIS OF THE DISCUSSED APPROACHES

The advancement of sleep spindle detection from traditional signal-based approaches to machine learning (ML) and deep learning (DL) techniques has significantly influenced adaptability, performance, and scalability. Each technique class exhibits distinct characteristics in terms of interpretability, accuracy, computational requirements, and suitability for real-world clinical applications. The evolution of sleep spindle detection techniques can be analyzed regarding their strengths, limitations, and practical implementation considerations. Below is a comparative breakdown of each approach:

A. TRADITIONAL SIGNAL-BASED APPROACHES

Traditional signal-based approaches primarily rely on bandpass filtering, fixed thresholds, time-frequency transforms (e.g., Fourier transforms, wavelets), and statistical rule-based heuristics.

- **Feasibility and Implementation Challenges:** Highly feasible for embedded systems and low-latency applications, but lacks scalability and is difficult to generalise across diverse datasets without manual tuning. These methods are not ideal for applications requiring high sensitivity or specificity.

TABLE 6. Summary of DL-Based techniques for sleep spindles detection.

Ref.	Objective	Dataset	Approach	Evaluation Metric
[104]	To develop a flexible, event-agnostic deep learning architecture (RED) for detecting sleep spindles and K-complexes using Bi-LSTM and CNN layers without fixed windowing.	MASS SS2 (15 subjects, annotated by E1 & E2, 256 Hz)	CNN + BiLSTM (RED-Time, RED-CWT); Time-domain and CWT-based input; Softmax output per 40 ms segment.	F1-score: 81.2% (SS-E1), 84.7% (SS-E2), 82.8% (K-Complex); Outperforms DOSED, Spinky, SpindleNet.
[96]	To create a U-Net-based model for high-resolution sleep spindle detection on single-channel EEG using weakly supervised learning.	MASS SS2, annotated by E1 and E2	U-Net CNN with adaptive feature fusion, trained with weak supervision and augmented data.	F1-score: ∼85%, IoU: 0.87; Outperforms A7, Lajnef, and Devuyst.
[103]	Develop a generalizable CNN-Bi-LSTM model for SS/KC detection across large datasets with rule-based pretraining and population analysis.	MASS SS2, MODA, NSRR (11k+), CAP	Multi-scale CNN + BiLSTM (SEED); pretrained using A7 rule-based labels; joint SS & KC detection.	F1: 86% (SS), IoU: 90%; generalizes across datasets with 10% fine-tuning data.
[99]	Detect spindles in noisy, weakly labelled EEG using a CNN-MIL framework with iterative label refinement.	MASS SS2 (19 subj.), DREAMS	CNN-MIL with bag-level training, weak supervision, and iterative label update.	F1: 59%, Acc: 95.3%; better than SpindleNet, Labelfix, Jiang.
[98]	Detect spindles from waveform images using a YOLOX object detection model (EEG → image).	MASS SS2 (1044 image segments, 5s each)	YOLOv4 and YOLOX (Tiny/SmallCoco) for bounding box prediction.	AP: 100% (IoU 0.5), 84.7% (IoU 0.8), Inference: 11ms/image.
[97]	Use weakly labelled EEG to train a CNN for per-sample spindle probability predictions.	MASS SS2, C3 channel, scored by 2 experts	CNN (5 conv layers) trained using MIL + loss on soft labels.	F1: 83%, AUC: 0.97; matches inter-expert agreement.
[106]	Compare the performance of DNN, CNN, LSTM, and CNN-LSTM models on sleep spindle detection using MASS SS2 EEG data.	MASS SS2 (19 subjects, Pz-CLE EEG)	CNN, LSTM, CNN-LSTM (Keras, Torch), Value-based baseline.	Best Accuracy: 67.15% (Torch CNN-LSTM); Value-based: 64.12%.
[105]	Evaluate deep learning models against human consensus in detecting sleep spindles from EEG.	Cz-A1 EEG from DREAMS (8 excerpts), annotated by crowd and experts,	CNN with weak supervision; training via human consensus labelling.	F1: ∼82%, AUC: 0.95; close to expert inter-rater agreement.
[109]	Detect spindles and K-complexes with end-to-end deep learning using raw EEG without feature engineering.	MASS SS2 (C3), 20s EEG segments	SSD-like CNN architecture with regression and classification heads; IoU-based label matching.	F1: 85% (spindles), 84% (KCs); outperforming Ferrarelli, Wendt, DOSED, Spinky.
[60]	Train a 1D-CNN to classify macro-sleep stages and detect CAP A-phases with spindle co-occurrence.	CAPSLPDB (108 PSGs), C3 EEG	6-layer CNN, dropout + dense layers, optimized for balanced/unbalanced CAP datasets.	F1 (CAP): 75.3%, Sleep stage Acc: 90.5%.
[106]	Compare CNN, DNN, LSTM, CNN-LSTM (Torch, Keras) models for spindle classification.	MASS SS2 (Pz-CLE), balanced spindle/non-spindle epochs	Torch CNN-LSTM (4 conv + FC layers), genetic optimization for epochs.	Best Accuracy: 67.15% (CNN-LSTM Torch).
[99]	Learn from imprecise labels using MIL with CNNs on spindle detection tasks.	MASS SS2, DREAMS	CNN instance-level scoring + bag-level aggregation.	F1: 59%, Accuracy: 95.3%; generalizes to other datasets.

- **Strengths:** These methods are lightweight and suitable for real-time or low-resource environments. They are based on well-understood signal properties, such as amplitude, frequency, and duration, making them easy to interpret and validate. These methods are also straightforward to implement using classical signal processing techniques.
- **Weaknesses:** The performance of the methods degrades significantly in noisy or artefact-prone EEG recordings, and traditional methods rely on rigid parameters, making them less adaptable to inter-subject and intra-subject variability. Another weakness of these methods is that they often fail to detect subtle or atypical spindles that do not conform to classical definitions.

Traditional signal-based approaches provide interpretability and simplicity; their performance mainly suffers from dependence on strict thresholds and manually set parameters. These methods work well with clean datasets and controlled environments, but their accuracy drops significantly in noisy or artefact-laden EEG recordings. Their inability to adjust to variability between and within subjects makes them less dependable for diverse populations. However, their computational speed and minimal hardware need still make them suitable for small-scale or resource-limited clinical settings where advanced infrastructure or large datasets are not available.

B. MACHINE LEARNING-BASED APPROACHES

Machine learning-based approaches address several limitations of traditional methods by leveraging statistical learning techniques.

- **Feasibility and Implementation Challenges:** These approaches are relatively easy to implement with standard toolkits (e.g., Scikit-learn, MATLAB) and suitable for mid-scale clinical or research applications. The performance of ML-based approaches may plateau if features are not optimally designed or if the dataset is small.

- **Strengths:** These approaches offer higher detection accuracy than traditional methods due to learning from data-driven patterns and can adapt to different EEG signal characteristics through well-engineered features. ML models like decision trees or SVMs allow partial insight into the decision process.
- **Weaknesses:** Domain expertise is required to design effective handcrafted features and is also sensitive to signal quality, class imbalance, and label noise. These approaches may require retraining or tuning for new datasets or populations.

ML-based approaches improve upon traditional methods by learning discriminative features, but their effectiveness heavily depends on the quality of datasets and careful feature engineering. The main advantage of ML is balancing better accuracy with moderate computational demands, making it suitable for mid-scale clinical settings. However, their dependence on handcrafted features limits scalability, and performance often stalls when datasets are small or imbalanced. In cases with limited annotated data or low-resource clinical environments, ML-based approaches may still be more practical than deep learning, offering a trade-off between performance and feasibility.

C. DEEP LEARNING-BASED APPROACHES

Deep learning-based approaches represent the most advanced category, offering fully automated feature learning from raw or minimally processed EEG signals. DL-based models such as BiLSTMs, CNNs, and U-Net architectures have proven state-of-the-art performance in spindle detection tasks.

- **Feasibility and Implementation Challenges:** The implementation of DL-based models are feasible in high-resource environments (e.g., research labs, hospitals with IT infrastructure) and also requires substantial expertise in deep learning, data augmentation, and model tuning. Explainability tools (e.g., Grad-CAM, SHAP) are necessary but add complexity to deployment.
- **Strengths:** Learns hierarchical features directly from raw or minimally processed EEG signals and outperforms traditional and ML methods in sensitivity, F1-score, and generalization. The approaches can also handle large-scale, noisy, and weakly labelled datasets.
- **Weaknesses:** DL-based approaches require GPUs or powerful servers for training and sometimes for inference. The models are often considered ‘‘opaque models’’ models, which may hinder clinical trust and acceptance and require large, annotated datasets for effective training and generalization.

DL-based models surpass both traditional and ML methods because they can automatically learn hierarchical features directly from raw EEG data and manage noisy, large-scale datasets. However, this superior performance depends mainly on having large, diverse, and high-quality annotated datasets, along with substantial computational resources. Their ‘‘black-box’’ nature also creates challenges for interpretability, which can limit clinical adoption. While DL approaches currently achieve top benchmark results, their complexity, high resource requirements, and interpretability issues mean they may not always be the most practical option in smaller clinics or for real-time bedside monitoring, where simpler ML or signal-based methods might still be more suitable.

Each approach has its strengths, weaknesses, feasibility and implementation challenges. The trend in spindle detection is moving towards more adaptive and data-driven solutions. The specific application requirements, availability of annotated data, computational resources, and the need for interpretability in clinical workflows should guide the choice of approach. Table 7 presents the summary of the discussed approaches, including implementation notes, strengths, and weaknesses.

VII. DISCUSSION

A. INTERPRETABILITY CHALLENGES IN DL-BASED SPINDLE DETECTION

While DL-based models have demonstrated strong performance in sleep spindle detection and classification, their black-box nature presents significant challenges for clinical integration. Clinicians require transparency in model decisions, particularly when these outputs are used to inform diagnoses, treatment choices, or long-term monitoring. Interpretability techniques are crucial in bridging the gap between high model performance and trustworthy clinical application.

1) GRAD-CAM FOR SPINDLE DETECTION

Gradient-weighted Class Activation Mapping (Grad-CAM) is a powerful visual explanation tool that highlights the regions of the signal most responsible for a model’s decision. In the context of spindle detection, a CNN can apply Grad-CAM to EEG signals to reveal temporal segments where the model detects spindle-like activity. As illustrated in Figure 6 (a), Grad-CAM activation overlays underscore a concentrated region of EEG activity, aligning well with known characteristics of sleep spindles in the sigma band (12–16 Hz). This visual alignment not only confirms that the model is focusing on physiologically meaningful patterns but also enhances its credibility among clinicians.

2) SHAP FOR EXPLAINING MODEL OUTPUT

Shapley Additive Explanations (SHAP) offer complementary insights by quantifying the influence of each input feature on the model’s output. In EEG-based detection tasks, features may include power in specific frequency bands (e.g., sigma, delta), statistical descriptors (e.g., skewness, entropy), or spatial-channel data. As illustrated in Figure 6 (b),

TABLE 7. Comparison of Traditional, ML, and DL Approaches for Clinical Use.

Aspect	Traditional Methods	Machine Learning (ML)	Deep Learning (DL)
Interpretability	High – rule-based	Medium – feature-based	Low – requires explainability tools
Computational Requirements	Low – lightweight	Moderate – CPU-based training	High – GPU required for training/inference
Data Requirements	Low – can work on limited data	Moderate – needs labeled features	High – requires large, labeled datasets
Ease of Integration	Easy – legacy systems compatible	Moderate – depends on infrastructure	Complex – often requires custom deployment
Scalability & Performance	Low to moderate	Moderate to high	High – state-of-the-art performance
Robustness to Noise	Low	Medium	High – if trained on noisy data

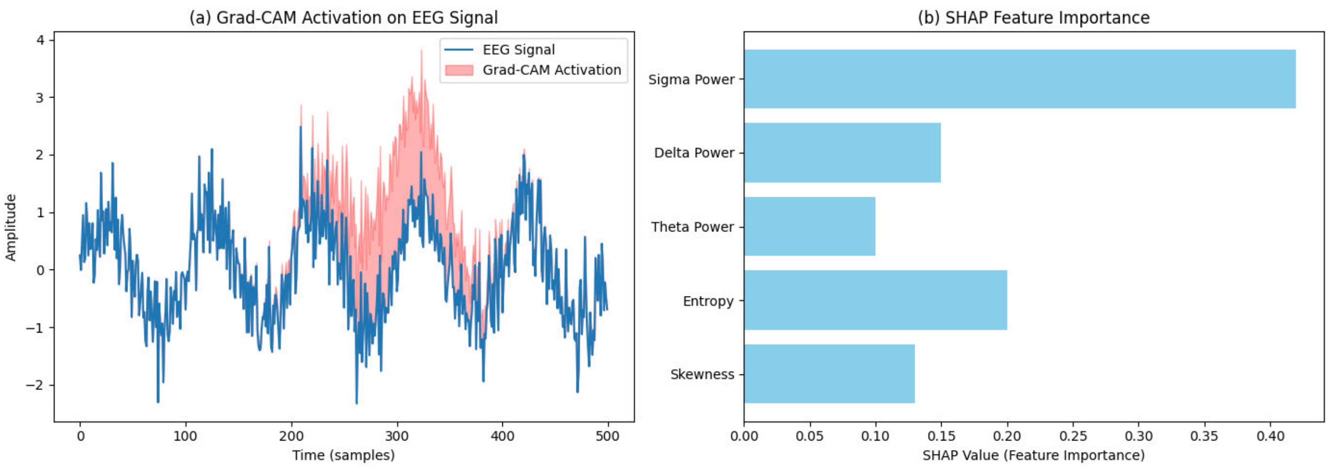

FIGURE 6. Interpretability of Deep Learning-Based Spindle Detection Using Grad-CAM and SHAP.

SHAP values indicate that Sigma Power has the greatest positive influence on the model's prediction, followed by Entropy and Delta Power. These quantitative attributions assist in validating whether the model is attending to medically relevant signals and provide deeper diagnostic interpretability.

3) CLINICAL RELEVANCE OF INTERPRETABILITY

Interpretability is more than a technical feature—it is a clinical necessity. Tools like Grad-CAM and SHAP help to demystify complex neural models by providing visual and quantitative justifications for predictions. This transparency is essential for building clinician confidence, navigating regulatory pathways, and facilitating the safe integration of DL-based spindle detectors into real-world sleep medicine workflows. By incorporating explainable AI components, future models can better align with both clinical expectations and ethical standards in healthcare technology.

B. IMPROVING GENERALIZABILITY ACROSS EEG DATASETS

A critical barrier in sleep spindle detection and classification is the limited generalisability of models trained on specific datasets. ML and DL-based models often demonstrate high performance on the datasets they were trained on but struggle to maintain accuracy when applied to different EEG channels, new subjects, or data collected under varying recording conditions. The data generalizability issue arises due to dataset bias—non-representative training data that limit the model's ability to generalise across real-world populations and clinical environments.

1) DOMAIN ADAPTATION TECHNIQUES

Domain adaptation techniques significantly reduce performance drops across datasets. These approaches aim to align the feature distributions between a source domain (e.g., the training dataset) and a target domain (e.g., the unseen test dataset). Techniques such as adversarial domain adaptation train a shared encoder that extracts domain-invariant features by minimising classification loss while simultaneously maximising domain confusion using a discriminator. In sleep spindle detection, adversarial networks can align EEG signal features across various institutions, recording setups, or patient populations.

2) DATA AUGMENTATION FOR EEG

Effective data augmentation is crucial for enhancing model robustness and minimising overfitting. In the realm of spindle detection, various augmentation strategies have demonstrated potential:

- Synthetic Spindle Injection: Artificial spindle events can be injected into real EEG signals by mimicking the characteristics of sigma-band frequency, duration, and amplitude. This approach enhances class balance and aids the model in learning more generalised spindle representations.

- Noise Perturbation and Channel Dropout: Introducing Gaussian noise or randomly zeroing out EEG channels during training can effectively simulate recording artefacts and electrode disconnections, thereby fostering resilience to real-world signal quality issues.
- Temporal Warping and Jittering: Slight distortions in time, such as stretching or compressing spindle windows, simulate natural variability in spindle duration and onset, making the model tolerant to temporal variations.

3) PROMOTING DATA DIVERSITY IN COLLECTION

The diversity of the training dataset significantly influences data generalisability. Models trained solely on data from a narrow demographic (e.g., healthy young adults) may struggle to perform effectively with infants, the elderly, or patients with neurological disorders. To address this:

- Standardise Multi-Site Data Collection: Collaborating across clinical sites to gather EEG recordings with consistent protocols can enhance data richness while preserving comparability.
- Include Diverse Demographics: Datasets should be collected across a range of ages, genders, ethnic backgrounds, and sleep-related clinical conditions (e.g., insomnia, PTSD, Alzheimer's disease).
- Label Harmonisation Across Raters: Consensus annotations or multi-expert labelled data can reduce variability and improve the quality of training labels, which is crucial for spindle detection models.

By integrating data augmentation, domain adaptation, and demographic diversity into spindle detection research, future models can achieve enhanced robustness, fairness, and real-world applicability. These strategies are not merely technical enhancements but essential steps towards developing clinically reliable and widely deployable EEG diagnostic tools.

C. CHALLENGES AND TRADE-OFFS IN CLINICAL IMPLEMENTATION OF DEEP LEARNING

Despite the strong performance of DL-based models in sleep spindle detection, their deployment in clinical settings presents several practical constraints. These limitations must be carefully considered when designing algorithms intended for real-world healthcare environments.

1) DEPENDENCE ON LARGE, LABELED DATASETS

Supervised deep learning models are data-hungry, necessitating large, diverse, and meticulously annotated datasets to learn generalised and accurate representations. In clinical neuroscience, such datasets are scarce due to the cost, time, and expertise required for manual spindle labelling. Furthermore, inter-rater variability and differing scoring standards across institutions further complicate model training and evaluation.

2) COMPUTATIONAL RESOURCE CONSTRAINTS

DL models, especially those based on convolutional and recurrent neural networks, generally require high-performance GPUs for both training and real-time inference. However, many hospital EEG systems function on resource-constrained hardware with limited processing capabilities. This results in a mismatch between model requirements and clinical infrastructure, particularly in low- to mid-resource settings where dedicated servers or cloud-based inference pipelines are not readily accessible.

3) EXPLAINABILITY VERSUS SIMPLICITY

DL models are frequently criticised as ''opaque models'' due to their lack of inherent interpretability. In contrast, traditional signal processing or classical machine learning methods (e.g., decision trees, SVMs) provide greater transparency, which is critical in medical contexts where explainability is not just preferred but required for regulatory approval and clinician acceptance. While explainability techniques like Grad-CAM and SHAP can assist, they add complexity and may not be fully trusted by non-technical users.

4) REAL-TIME AND EDGE DEPLOYMENT

Low-latency and real-time performance are essential challenges for integrating automated sleep spindle detection into a clinical setting. The current traditional offline models are accurate but require significant computational resources and are unsuitable for bedside monitoring or portable sleep devices. Recent research has introduced lightweight models that can run on embedded systems or edge devices without depending on high-performance servers. Edge deployment provides several advantages for automatic sleep spindles detection: (i) enhanced privacy and security, as sensitive patient data stays on the device; (ii) lower bandwidth needs, since raw EEG doesn't have to be continuously streamed to central servers; and (iii) reduced latency, allowing real-time visualisation of spindles during polysomnography. Detection methods such as model quantisation, pruning, and knowledge distillation have been examined to decrease computational load and model size while maintaining detection accuracy. Despite the advantages of edge deployment, significant limitations persist. Clinical-grade embedded solutions must find a balance between energy efficiency and dependability, especially for wearable EEG headbands or home-based monitoring platforms. Furthermore, hardware inconsistencies across hospitals and a lack of standardised toolchains for medical edge-AI systems present practical challenges. Tackling these issues will be crucial to transition from research prototypes to routine clinical use of real-time spindle detection.

VIII. CHALLENGES AND OPEN ISSUES

Despite the substantial advancements in sleep spindle detection, several challenges and open issues remain that limit the widespread clinical and practical deployment of current approaches.

- Lack of Interpretability: Based on the critical evaluation of existing research studies, we identified that DL-based methods often act as "black-box" models. Their decisions are difficult to interpret and validate, which reduces clinical trust and impedes regulatory approval [97], [100].
- Variability in Spindle Morphology: Based on the analysis of [48] and [69], sleep spindles demonstrate significant inter- and intra-individual amplitude, duration, and frequency variability. These variations pose challenges for ML and DL algorithmic generalization across different subjects, age groups, and EEG channels.
- Limited Availability of Labelled Data: After the comprehensive evaluation of existing datasets, we identified that there is a need for high-quality and annotated EEG datasets for model training and testing. The publicly available datasets have limited subject diversity and channel configurations, which restrict the development of highly generalizable models, including ML and DL. This is especially critical for DL, which requires extensive labelled data for robust training [96], [104].
- Annotation Subjectivity and Label Inconsistency: Manual annotation by human experts and researchers remains the gold standard for supervised model training. Nevertheless, even expert scorers often disagree with inter-rater reliability (Cohen's Kappa) around 0.52 [48]. This subjectivity negatively impacts model training, label noise, and evaluation.
- Multi-event Co-detection: Sleep EEG signals may contain overlapping events such as slow waves and K-complexes. Distinguishing spindles from other events in multi-label settings or during temporal co-occurrence remains underexplored [104], [109].
- Class Imbalance: The research survey revealed that in typical EEG recordings, sleep spindles are rare, resulting in imbalanced class distributions. This imbalance can bias models toward non-spindle classifications, lowering sensitivity and F1-score [83].
- Overfitting and Generalization: Based on the data interoperability, we identified that many ML and DL models demonstrate promising performance on specific datasets but often fail to generalise across different populations or unseen data without retraining or fine-tuning [82].
- Real-Time Implementation and Power Efficiency: Some clinical and wearable applications require real-time detection with low power consumption. Designing accurate and computationally efficient models remains an open challenge, especially for embedded or edge devices [71].

Addressing the above-discussed challenges is critical for moving sleep spindle detection algorithms from research settings to real-world clinical and neurotechnological applications.

IX. FUTURE DIRECTIONS

To overcome the above-discussed challenges and enhance the utility of spindle detection systems, several future research directions are proposed based on the state-of-the-art:

- Personalized Spindle Detection: Based on the survey discussion, we identified that individualised spindle detection models that dynamically adapt to user-specific EEG patterns can improve accuracy and clinical relevance. Integrating personal neuro profiles could further tailor detection parameters [110].
- Few-Shot and Semi-Supervised Learning: The survey identified that integrating few-shot or semi-supervised learning methods can reduce dependency on large, labelled datasets and better handle label noise, particularly useful for underrepresented clinical populations [111].
- Development of Larger and More Diverse Datasets: Based on the existing research, the survey identifies that future efforts should prioritise building publicly available, large-scale, multi-channel EEG datasets with diverse subject populations and consistent expert annotations. This will support the training and validation of generalizable models [112].
- Explainable AI (XAI) in Spindle Detection: Based on the interpretability section, we identified that future spindle detection models should incorporate interpretability frameworks like attention mechanisms, saliency maps, and layer-wise relevance propagation to improve transparency and foster clinical trust [113].
- Federated Learning and Privacy-Preserving AI: Future research should also focus on emphasising federated learning and privacy-preserving AI to foster multi-centre collaboration without depending on centralised data sharing, which is often restricted by ethical and legal constraints in healthcare. Federated learning frameworks allow models to be trained across institutions while keeping patient data local, thereby improving the generalisability and diversity of training datasets without compromising privacy.
- Incorporating Multimodal and Contextual Information: Combining EEG with other physiological signals (e.g., EOG, EMG, HRV) or sleep context (e.g., sleep stages, circadian rhythms) may enhance detection performance and robustness [114].
- Multi-task Learning Frameworks: The survey identified that jointly training models to detect multiple sleep micro-events (e.g., spindles, K-complexes, slow waves) can enhance temporal resolution, reduce false positives, and more accurately mimic human scoring [115].
- Transfer Learning and Domain Adaptation: Leveraging transfer learning techniques can enable the adaptation of pre-trained models across different populations and recording setups with minimal retraining. Domain adaptation strategies can further reduce performance drop-offs on unseen data.

TABLE 8. List of Abbreviations.

Abbreviation	Description	Abbreviation	Description
ML	Machine Learning	DL	Deep Learning
ATM	Air Traffic Management	TCAS	Traffic Alert and Collision Avoidance System
NREM	Non-Rapid Eye Movement	ASD	Autism Spectrum Disorder
TEO	Teager Energy Operators	EEG	Electroencephalogram
RF	Random Forests	SVM	Support Vector Machines
K-NN	K-Nearest Neighbors	RNNs	Recurrent Neural Networks
MIL	Multiple Instance Learning	FPR	False Positive Rate
FNR	False Negative Rate	ASSD	Automated Sleep Stage Classification
MCC	Matthews Correlation Coefficient	MASS	Montreal Archive of Sleep Studies
SDB	Sleep Density Dataset	DDA	Delay Differential Analysis
FixF	Fixed Frequency	IAM	Individual Adjustment Method
PSD	Power Spectral Density	SEF	Spectral Edge Frequency
SoC	System-on-hip	SST	Synchrosqueezing Transform
EMD	Empirical Mode Decomposition	CWT	Continuous Wavelet Transform
CD	Complex Demodulation	SWPE	Sliding Window-Based Probability Estimation

- Edge AI and Real-Time Deployability: The survey concludes that designing lightweight models compatible with mobile, embedded, and wearable devices will accelerate clinical translation, especially in home-based or telemedicine applications [116].

Continued interdisciplinary collaboration between the signal processing, neuroscience, and AI communities is essential to pushing the boundaries of automated sleep spindle analysis and enabling its integration into clinical diagnostics and brain-computer interfaces.

X. CONCLUSION

A. SUMMARY OF KEY FINDINGS

The proposed research survey provides a comprehensive overview of sleep spindle detection methods, classifying them into traditional, machine learning, and deep learning techniques. Key findings reveal that while traditional techniques offer interpretability and computational efficiency, they experience limited accuracy. ML-based techniques enhance adaptability and performance but require carefully engineered features. DL-based techniques achieve the highest accuracy and robustness, particularly on large datasets; however, challenges remain in terms of interpretability and data dependency.

B. IMPLICATIONS FOR SLEEP RESEARCH AND CLINICAL APPLICATIONS

This survey has significant implications for sleep research and clinical applications. Automated spindle detection can potentially improve diagnostic workflows, support neurocognitive studies, and improve our understanding of sleep physiology. However, adoption in clinical practice requires accurate, yet also explainable and generalizable, models across diverse populations.

C. FINAL THOUGHTS AND RECOMMENDATIONS

This survey highlights the advancements made in the field and emphasizes the need for the continued development of models that balance performance with clinical interpretability. Future work will focus on implementing and evaluating ML-based spindle detection techniques using state-of-the-art EEG datasets, such as MASS and DREAMS, to contribute practical, scalable, and transparent tools for sleep research and healthcare.

D. LIMITATIONS

Although this review follows PRISMA guidelines and uses a systematic search strategy across multiple databases, certain limitations should be acknowledged. Firstly, only studies published in English were included, which may exclude relevant research published in other languages. Secondly, proprietary and non-public datasets, including clinical EEG datasets not accessible for research, were excluded due to access restrictions. Thirdly, publication bias might be present, as studies reporting negative or non-significant results are less often published in indexed journals. Lastly, as the field advances rapidly, some recent preprints and unpublished works may not have been captured at the time of review. These factors should be considered when interpreting the findings and trends reported in this survey.

Table 8 represents the abbreviations used in the survey paper.

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